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A Review:Generative Artificial Intelligence

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Abstract— Generative Artificial Intelligence (GenAI) is increasinglybeingadoptedacrossdiversefields,from industrial applications to academic research. These systems are primarily operated through prompts— user-provided instructions that guide the AI in performingspecifictasks.However,duetothefield's recent emergence, prompt engineering still lacks standardized terminology and clearly defined boundaries. This paper aims to bring structure to this evolving domain by proposing a classification of different prompting strategies and analyzing their real-world applications. It offers a comprehensive glossary of frequently used terms, a well-organized framework encompassing various prompting techniques across different input types, and best practices for working with large language models (LLMs) such as ChatGPT. The study also includes a meta-analysis of existing literature related to text- based prompting, positioning this work as a foundational reference in the area.
Keywords—Aboutfivekeywordsin alphabetical order, separated by comma

I. INTRODUCTION

Transformer-based LLMs have become integraltovariousapplications,rangingfrom personal use cases and enterprise tools to academic research. Thesemodelstypicallyoperatebyrespondingtouser inputs known as prompts, which may be in the form of questions, commands, or other instructions.While prompts are most often text-based, they can also includemultimediainputssuchasimages,audio,and video. One of the key strengths of LLMs is their ability to understand and respond to natural language prompts,whichcontributestotheiradaptabilityand broadapplicability.Theeffectivenessofthesemodels often hinges on the quality and structure of the prompts used. Well-crafted prompts generally

Despite its growing relevance, prompt engineering remains a relatively nascent discipline with ongoing debates and inconsistencies in how techniques are defined and applied. To address this, our study undertakes a detailed review of the current methods andterminologyassociatedwithpromptengineering. The goal is to offer a clearer, more systematic understanding of the field by developing a shared vocabulary and structured categorization of prompting approaches.

WhatisaPrompt?–Apromptreferstoanytype of inputprovidedtoagenerativeAIsystemtodirectits response. This input can take the form of text, images, audio, or other data types. For example, a prompt might be a request like "Compose a three-paragraph email for an accounting firm's marketing campaign," an image with a question overlaid, or an audio clip with instructions like "Summarize this meeting." Whilemostcurrentpromptsaretext-based,thiscould change as multimodal models capable of interpreting multiple types of media become more prevalent.

Tosimplifypromptgeneration,developersoftenuse prompt templates—predefined structures where placeholders are filled with specific content to form complete prompts. For instance, a template might say: "Write a poem about the following topic: {USER_INPUT}," where {USER_INPUT} can be dynamically replaced with different themes. This

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makespromptdesignmoreefficientandscalablefor repeated tasks.

AMeta-Analysisof Prompting SystematicReview Process

To develop a credible and high-quality dataset of academicresourcesforthisstudy,weimplementeda systematic literature review strategy inspired by PRISMA guidelines. This structured approach involved
multiple stages to ensure a consistent and comprehensiveselectionofrelevantstudies.The resulting dataset, along with detailed metadata documentation, is publicly accessible via HuggingFace.
We gathered research papers primarily from databasessuchasarXiv,SemanticScholar,andthe In-Context Learning (ICL)
In-ContextLearningreferstothecapacityof generative AI systems to perform tasks by interpreting
examplesorinstructionsembeddedwithinthe

promptitself—withoutrequiringmodelretrainingor weight adjustment (Brown et al., 2020; Radford et al., 2019b). These tasks may be inferred through demonstrations(Figure2.4)ordirectives(Figure 2.5).
However,theterm"learning"canbemisleadingin this context; ICL often simply involves task specification rather than the acquisition of new skills—many capabilities may already exist in the model'strainingdata(Figure2.6).Formoredetail, see
AppendixA.9.Thereisongoingresearchinto refining
andbetterunderstandingICL(Bansaletal.,2023).

ThoughtGeneration

Thisapproachinvolvespromptinglanguagemodels to
explicitlyarticulatetheirreasoningwhiletacklinga problem (Zhang et al., 2023c). Chain-of-Thought (CoT) prompting, introduced by Wei et al. (2022b), uses a few-shotmethodtoencouragemodelstorevealtheir logical process prior to giving a final answer. This method,alsoknownasChain-of-Thoughts(Tutunov et al.,2023;Bestaetal.,2024;Chenetal.,2023d),has proven effective for enhancing performance on reasoning and mathematical tasks. In the original demonstration (Wei et al., 2022b), the prompt includes a sample with a question, a reasoning path, and the correct response.

DecompositionTechniques

Researchershaveextensivelyexploredthestrategyof breaking complex problems into simpler sub-tasks— a method that mirrors human problem-solving and benefitsGenAIsystemsaswell(Pateletal.,2022). WhileCoToftenresultsinimplicitdecomposition, explicitly fragmenting atask can further enhancea model's effectiveness.

Least-to-MostPrompting

Zhouetal.(2022a)proposedamethodthatbeginsby instructing the model to deconstruct a complex task into smaller, manageable sub-tasks without solving them immediately. These sub-tasks are then addressedoneatatime,witheachsolutionappended to the prompt before moving on to the next. This approach has shown marked improvements in tasks involving logic, symbolic reasoning, and compositional
generalization.

DecomposedPrompting(DECOMP)

Khotetal.(2022)introducedDECOMP,afew-shot prompting method that demonstrates the use of specific tools or functions—such as string

manipulationorwebsearch—bysplittingproblems into sub-tasks delegated across different AI operations. This modular strategy outperformed Least-to-Most prompting in various scenarios, emphasizing the benefits of functional task decomposition.

Plan-and-SolvePrompting

Wangetal.(2023f)advancedthisideawitharefined Zero-Shot Chain-of-Thought prompt: "Let's first understand the problem and devise a plan to solve it. Then, let's carry out the plan and solve the problem step by step." This method encourages clearer, more structured reasoning and has outperformed traditional Zero-Shot CoT approaches on several benchmark reasoning tasks.

Tree-of-Thought(ToT)(Yaoetal.,2023b),also known
asTreeofThoughts,(Long,2023),createsatree-like search problem by starting with an initial problem thengeneratingmultiplepossiblestepsintheformof thoughts (as from a CoT). It evaluates the progress each step makes towards solving the problem (through prompting) and decides which steps to continue with, then keeps creating more

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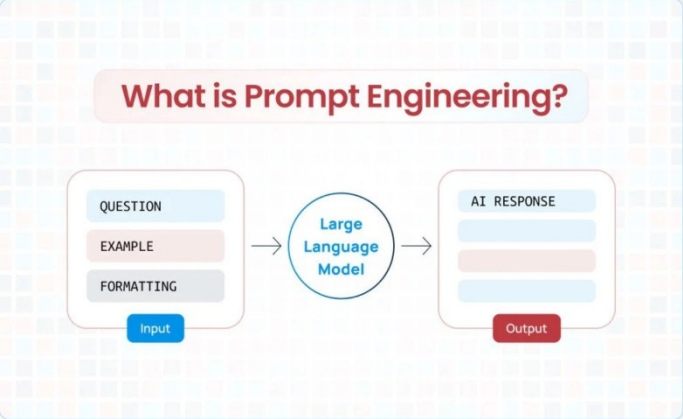
thoughts.
ToTisparticularlyeffectivefortasksthatrequire search and planning.
Recursion-of-Thought(LeeandKim,2023)is similar
to regular CoT. However, every time it encounters a complicated problem in the middle of its reasoning chain,itsendsthisproblemintoanotherprompt/LLM call. After this is completed, the answer is inserted into the original prompt. In this way, it can recursively
solvecomplexproblems,includingoneswhichmight otherwise run over that maximum context length.
This
method has shown improvements on arithmetic and algorithmic tasks. Though implemented using fine- tuning to output a special token that sends sub- problem into another prompt, it could also be done onlythroughprompting.Program-of-Thoughts(Chen et al., 2023d) uses LLMs like Codex to generate programming code as reasoning steps. A code interpreter executes these steps to obtain the final answer. It excels in mathematical and programming- related tasks but is less effective for semantic reasoning tasks.
Faithful Chain-of-Thought (Lyu et al., 2023) generates a CoT that has both natural language and symbolic language (e.g. Python) reasoning, just like Program-of-Thoughts.However,italsomakesuseof different types of symbolic languages in a task- dependent fashion.



II. CONCLUSION

answer.Itexcelsinmathematicalandprogramming- related tasks but is less effective for semantic reasoning tasks.
Faithful Chain-of-Thought (Lyu et al., 2023) generates a CoT that has both natural language and symbolic language (e.g. Python) reasoning, just like Program-of-Thoughts. However, it also makes use of different types of symbolic languages in a task- dependentfashion.meetings continueto be organized.
However, during this process, it was easier and more comfortable for some people to work online; therefore, theirinterestinMetaversehasincreasedconsiderably.Itis a matter of curiosity whether people will accustom themselves to such a virtual environment that offers positive and negative results. In addition to psychological issues followed by the Metaverse, it is also discussed that somephysicalproblemsmayoccurontheway.According to Kuş (2021), users may use some virtual reality head- suits to move in the Metaverse virtual world, resulting in some actions that can harm themselves in the physical world.ThisraisesthepossibilitythatMetaversecouldbea physical disadvantage, too. Until a few years ago, the advertising industry differed from the current one. Brands used to promote their products through television and radio, now they can promote them on the internet and reach their users easily and at lower costs. Since people spend most of their time online, it makes more sense to advertise and promote products online. As Bilgici and Şisman (2022) mentioned in their study, social media advertisingwillnowshiftfromsocialmediachannelssuch asTwitter,Instagram,etc.totheMetaverseworldwiththe emergence of the concept of 'metafluence' and brand strategies will now start to be built on 'metafluence'people. The concept of the Metaverse, both with its positive and negative aspects, is slowly entering human lives and significantly affecting their traditional lifestyle you are working with constitute a good
representation of that problem. It is better to start
withsimplerapproachesfirst,andtoremainskeptical of claims about method performance. To those alreadyengagedinpromptengineering,wehopethat our taxonomy will shed light on the relationships

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